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Sensing noise exposure and its inequality based on noise complaint data through vision-language hybrid method

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A R T I C L E I N F O

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A B S T R A C T

This study seeks to reveal urban noise exposure patterns and inequalities using noise complaint data and vision-language hybrid method. By applying a natural language processing model to 17,243 noise complaint records, we uncovered distinct patterns of traffic, industrial, and living noise exposures across residential communities. Our analysis of street view images near complaint locations, utilizing a Residual Network (ResNet) model and Class Activation Mapping (CAM), identified the key environmental elements of different noise sources. Notably, our assessment of noise exposure inequality across 9791 communities yielded a counterintuitive finding: contrary to previous studies in Western contexts, rich communities in China experience higher and more unequal noise exposure compared to average communities, with Gini coefficients exceeding 0.8. This unexpected result likely stems from China's unique rapid urbanization process. Our use of crowdsourced complaint data aligns more closely with human subjective perceptions of noise, offering a novel perspective on noise exposure inequality. These findings challenge existing assumptions about the relationship between socioeconomic status and environmental quality in urban China, and have significant implications for urban planning and noise management strategies in rapidly developing cities.

1. Introduction

The World Health Organization (WHO) considers noise the third most harmful form of pollution (after air and water pollution), which is highly associated with various health issues including cardiovascular disease, sleep disorders, depression, and psychological stress (Basu et al., 2021; Vienneau et al., 2022). People who live in urban areas may be exposed to complex noise shaped by the transportation system, construction and industrial activities, high population density and other sources (McAlexander et al., 2015). As a result, the noise exposure of urban residents may have various adverse health impacts on them (e.g., road traffic is associated with people's psychological stress, heart disease, and sleep disturbance) (Münzel T et al., 2021; Lee PJ et al., 2019; Marquis-Favre C et al., 2023).

However, past studies have overlooked that different individuals may perceive the same noise differently. For instance, even when the noise level at a location is very high (e.g., 70 dB(A)), it may be acceptable for some people while others may find it disturbing. The subjective perception of noise refers to how individuals experience and react to noise, which can vary widely based on factors such as gender, age, and income level (Carrier et al., 2019; Peng et al., 2022; Tong & Kang, 2021b). Certain population groups, such as the elderly, children, and those with pre-existing health conditions, are more physiologically vulnerable to the effects of noise. Moreover, when comparing different residential communities (e.g., rich and poor communities), it becomes apparent that people have entirely different perceptions of noise, possibly due to disparity in geographic location or building materials (e.g., sound-proofing materials), highlighting a potential inequality in people's noise exposure (Riedel et al., 2022; Nega, T. H et al., 2013; Carrier, M et al., 2016). Lower-income individuals and communities may have more noise exposures. For example, economically disadvantaged communities are often located closer to major traffic routes and industrial areas, where noise exposure is more severe (Carrier et al., 2019; Collins et al., 2019, 2020; Margaritis et al., 2018). This geographic and socioeconomic disparity highlights the need to study noise exposure through the lens of environmental equity. In this research, environmental equity refers to the fair distribution of environmental benefits and burdens across different social groups, without discrimination based on race, income, or other socioeconomic factors.

Further, the high cost of static noise monitoring equipment limits its

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coverage and the availability of noise data for mapping noise over wide areas. A previous study showed that even with the deployment of 144 fixed noise monitoring stations, the basic coverage of the noise map remains very limited in metropolitan areas (Xu et al., 2022). Additionally, studies such as those by Licitra et al. (2022) on noise source predominance maps and Fredianelli et al. (2022) on traffic flow detection using machine learning, while technologically advanced, still face challenges in data acquisition and accuracy in practical applications. Alías and Alsina-Pagès (2019) reviewed the use of wireless acoustic sensor networks for environmental noise monitoring in smart cities, highlighting their potential but also noting limitations in equipment costs and data processing. Liu, Ma, Shu, and et al (2020) and López, Alonso, Asensio, and Suárez (2020) discussed IoT technologies and DSP-based acoustic sensors, respectively, which improve real-time monitoring and accuracy but still encounter issues with large-scale deployment and maintenance.

Such device-based methods for monitoring urban noise have faced numerous challenges, such as difficulty in differentiating different types of noise (i.e., noise classification) and identifying the sources of noise. For instance, some studies have treated urban noise as a generalized measure (i.e., dB(A)), with noise levels exceeding 70 dB being deemed harmful (mentioned above). It is important to note that individuals may experience positive emotions during noisy concerts or similar events (Tao et al., 2020). Thus, categorizing and identifying the types of noise and their sources is imperative.

Therefore, this study seeks to address the following questions: **1)** How can noise be effectively and affordably identified and mapped from a human-centered perspective? **2)** What are the visual causal factors of different types of noise? **3)** Are there inequalities in noise exposure between different social groups (based on their income level) in different residential communities?

To address these questions, it is crucial to first understand the current state of research on noise perception mapping and its implications. We will review the relevant works of literature, respectively.

1.1. Mapping the subjective perception of noise

With over 40% of the world's population affected by noise exposure risks (Basu et al., 2021), noise pollution is one of the most serious urban malaises. It has been observed to be highly associated with mental disorders such as anxiety and depression, as well as cardiovascular diseases. However, mapping different categories of noise and people's noise exposure on a large scale is challenging. Current methods mainly include device-based and model-based approaches (Lan & Cai, 2021). The former requires deploying a large number of sensor devices (Yin et al., 2020) to obtain fine-grained noise maps through real-time noise monitoring data (Lan et al., 2024a). However, this method is costly and difficult to implement on a large scale. For example, to create a noise map of a city center, hundreds of stations need to be deployed to achieve basic coverage (Xu et al., 2022).

To address this issue, model-based methods of noise mapping were often used. Some scholars construct an urban noise model (LUNOS) based on linear models. The model establishes a connection between land use and noise exposure through regression functions, using environmental factors to fit it (Xie et al., 2011). This method is simple and has low accuracy. With the development of artificial intelligence, some scholars have applied multimodal techniques (Huang et al., 2024; Zhao et al., 2023; Zhuang et al., 2024) to derive noise levels from extensive street view image data (Verma et al., 2020; Zhang et al., 2022). Zhuang et al. (2024) suggested that few studies integrated auditory and visual perceptions to understand the human sense of place. To address this gap, they proposed a soundscape-to-image diffusion model, a generative AI model supported by large language models (LLMs), to visualize soundscapes by generating street view images. This facilitates the convenient capture of soundscapes. Zhang et al. (2022) used 500,000 images in Singapore and Shenzhen and obtained a correlation coefficient of 0.48 between soundscapes and street views. The application of AI technology allows us to sense urban noise on a large scale with low cost and high precision.

However, this method of obtaining noise maps is purely objective, without considering the impact of perceived noise on human well-being, especially the noise exposure of residential communities (Huang & Kwan, 2022). Therefore, some researchers have incorporated dynamic population distribution (Lan et al., 2024b), different age groups (Wang et al., 2022), and income levels (Yang et al., 2020) into noise analysis.

Interestingly, recent researchers have found that noise complaint data more closely reflect humans' actual perception of noise exposure (Ramphal et al., 2022), whose distribution is also strongly associated with people's income level (Peng et al., 2022; Tong & Kang, 2021b). For instance, poorer areas often have higher rates of noise complaints, and the locations of noise complaints are closely related to the surrounding built environment (Zijlema et al., 2024) and urban morphology (Tong & Kang, 2021a). Given that noise complaint data can more accurately reflect subjectively significant noise exposure by combining semantic information from noise complaints (i.e., subjective perspective) with environmental features (i.e., objective perspective), it can serve as an effective tool for noise perceiving and mapping.

1.2. Inequality in noise exposure

There is ample evidence that noise exposure is unequal among different social groups (Havard et al., 2011; Hosking et al., 2022). This inequality often exists among communities with different income levels (Dreger et al., 2019; Johnston et al., 2020; Tonne et al., 2018). And this inequality disproportionately affects vulnerable populations and racial minorities. For instance, Carrier et al. (2016, 2019) highlighted significant disparities in road traffic noise exposure among vulnerable populations in Montreal. Similarly, Collins et al. (2019, 2020) documented social disparities in noise exposure at public schools and residential areas in the United States, revealing that children in lower-income neighborhoods are more likely to be exposed to higher levels of transport noise. Nega et al. (2013) demonstrated the unequal distribution of traffic noise in the Twin Cities, Minnesota, emphasizing the need for targeted policies to protect vulnerable groups from the adverse effects of noise. These studies underscore the importance of examining noise exposure through the lens of environmental justice and equity, as certain groups live in noisier environments and benefit less from noise protection measures (Potvin et al., 2019).

In the context of China, concrete evidence on noise exposure and social inequality is still lacking (Liao et al., 2023). And the effects of high-density residential areas on noise exposure are noteworthy. The dense layout of numerous high-rise residential and commercial buildings not only reflects and amplifies noise but also increases noise generation due to high levels of traffic, business operations, and industrial production (Lam & Chung, 2012). Additionally, the amplifying and blocking effects of buildings on noise are significant factors (Yuan et al., 2019).

While past studies have examined the relationship between noise exposure and social inequality, most focused on static noise exposure assessments, overlooking the distance between different types of noise sources and residential communities (Yildirim & Arefi, 2021; Audrin et al., 2022). For example, Pinsonnault-Skvarenina et al. (2021, 2022, 2024) provide valuable insights into community responses to noise from large-scale construction projects, highlighting the importance of effective noise mitigation strategies.

Based on this research gap, our study aims to analyze the disparities in noise exposure among different residential communities, considering the distance effect and types of noise sources. This approach will provide a more nuanced understanding of how noise exposure varies across different social groups and geographic contexts, contributing to the broader discourse on environmental equity and justice.

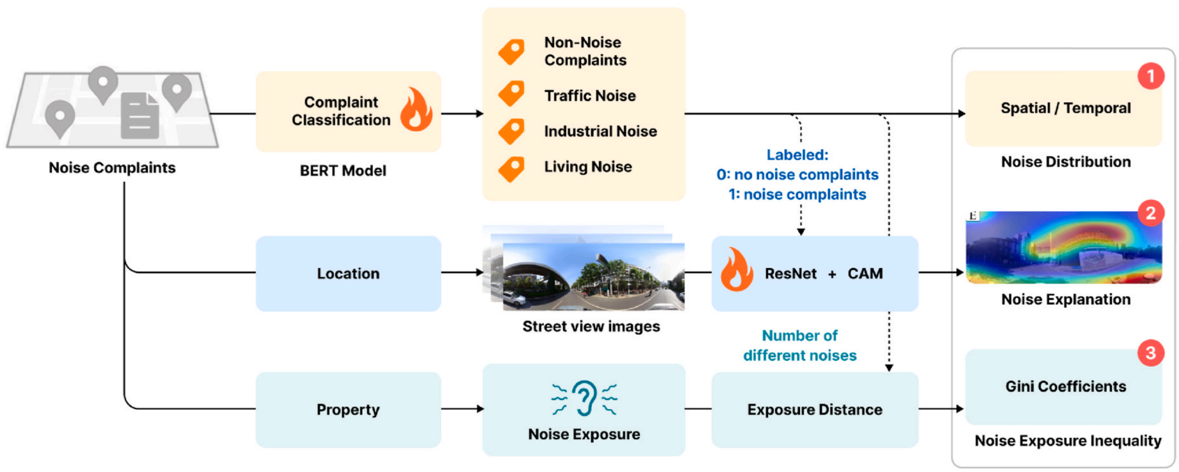

Fig. 1. Research framework. The three main tasks of this study are 1) collecting noise complaint data using a natural language model (the BERT model) to identify and classify different types of noise exposure (i.e., traffic noise, industrial noise, and living noise); 2) training a ResNet model using street view images, which were collected based on the locations of the noise complaints, along with corresponding noise resource labels (i.e., ''0'' represented no noise complaints and ''1'' represented noise complaints). The aim of this part is to identify different noise resources from various environmental features; and 3) assessing the levels of noise exposure and its inequalities among different residential communities.

1.3. The impact of noise pollution on people's health

Noise exposure is a significant environmental concern with wide-ranging health implications. Preventing noise exposure is crucial to avoid levels that lead to complaints and adverse health effects. Studies indicate a strong relationship between noise complaints and socio-economic factors, highlighting the importance of addressing these issues in urban planning (Tong & Kang, 2021; Licitra et al., 2019). Health impacts of noise exposure include sleep disorders (Muzet, 2007), learning impairments in children (Erickson & Newman, 2017), and cardiovascular issues such as hypertension and ischemic heart disease (Dratva et al., 2012; Van Kempen & Babisch, 2012; Bluhm et al., 2007). Additionally, noise exposure can lead to elevated diastolic blood pressure (Lee et al., 2019; Petri et al., 2021), reduced cognitive performance (Vukić et al., 2021; Rossi et al., 2018), and increased annoyance (Miedema & Oudshoorn, 2001; Fredianelli et al., 2019; Licitra et al., 2016). Factors such as peak levels, temporal variations, amplitude modulation, impulsivity, and frequency distribution significantly impact noise perception (Redel-Macías et al., 2019; Marquis-Favre et al., 2023; Lavandier et al., 2022).

Modern technology plays a crucial role in noise management, particularly in smart cities. Innovative approaches, such as real-time evaluation, improved monitoring stations, and artificial intelligence applications, are shaping the future of environmental acoustics (Asdrubali & D'Alessandro, 2018; Fredianelli et al., 2022). Effective noise mitigation strategies involve comprehensive noise mapping, action plans, and specific measures like low noise pavements and electric vehicles (Licitra et al., 2023; Liu, Ma, Shu, & et al, 2020; López, Alonso, Asensio, & et al, 2020). Specific noise sources, including road traffic (Cueto et al., 2017; Ruiz-Padillo et al., 2016), railway traffic (Bunn & Trombetta Zannin, 2016), airports (Gagliardi et al., 2018; Iglesias-Merchan et al., 2015), port activities (Fredianelli et al., 2022; Borelli, 2019), and industrial noise (Atmaca et al., 2005), each require targeted interventions to mitigate their impact effectively, which is the research motivation of this paper.

2. Methodology

The study area for this research is located in the central district of Wuhan City in China. Wuhan is a major metropolitan area in central China with a high density of traffic and industrial activities, contributing to various environmental challenges, including noise pollution.

This study has three main research tasks (Fig. 1): 1) Identifying and mapping noise effectively and affordably from a human-centered perspective. 2) Analyzing the sources of different types of noise and their impact on urban residents. 3) Examining noise exposure inequalities among various residential communities based on income level. Thus, the first research task is to train a noise complaints classifier based on the BERT semantic pre-trained model, which automatically identifies different types of noise exposure, including traffic noise, industrial noise, and living noise. The second task of this study is to conduct an interpretable noise source analysis using the Residual Network (ResNet) model and the Class Activation Mapping (CAM) method to identify environmental features most associated with noise. The third task focuses on examining inequality in noise exposure by assessing the impact of different types of noise on communities with different socioeconomic statuses (i.e., rich, average, and poor communities) using the Gini coefficient.

2.1. Data collection and processing

We obtained residents' complaint data, socioeconomic data, street view images, population data, and building density data from various sources. Specifically, the noise complaint data, the primary data source used in this study, came from the Wuhan Government's website[1] and includes about 287,529 complaint records from October 2020 to September 2021. This data is similar to the 311 hot-line data in the U.S. (Xu et al., 2017) and includes the following information: 1) The latitude and longitude of the complaint events, which were uploaded by users themselves to ensure precise geographic localization of each complaint; 2) Complaint content, which recorded the specific grievances of the complaint in detail; and 3) The response content and the time of the complaint, including the time the complaint was submitted by a resident and the response time from the management departments.

Further, from the Lianjia website,[2] we obtained the socio-economic data of each of the 9,791 residential communities in the study area. This data includes key information such as the location and housing price of each residential community, reflecting its income level. In addition, we collected 15,550 street view images around the noise complaint locations to facilitate the discovery of the implicit

[1] https://liuyan.cjn.cn/.
[2] https://m.lianjia.com/.

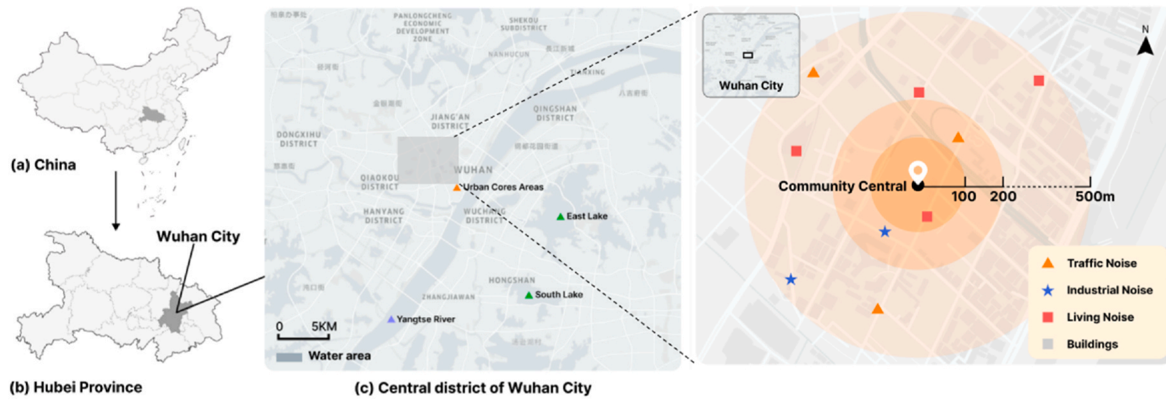

Fig. 2. Research Map and Calculating noise exposure and building density. Schematic representation of building density and noise exposure around residential communities, with a buffer zone radius from 100 to 500 m. The legend denotes traffic noise (triangle), industrial noise (star), and living noise (square), while gray squares indicate buildings.

relationships between environmental features and noise pollution. Moreover, the population and building density data were respectively sourced from the WorldPop grid and Baidu electronic maps, which are widely used in related research (Zhang, Chen, Du, et al., 2021).

2.2. Noise complaints classification based on the BERT model

Noise complaints in this study are categorized into three types: traffic noise (including vehicle honking, disturbance by dump trucks, etc.), industrial noise (including noise from construction, factory production, etc.), and living noise (such as square dancing, loud shouting, party activities, etc.). However, manually labeling the large number of noise complaints (approximately 287,529 complaint records) can be time-consuming and inefficient. Thus, we used a Natural Language Processing (NLP) method to develop an automatic noise complaint identification model. The BERT (Bidirectional Encoder Representations from Transformers) is a typical model in the field of NLP. By learning deep language representations from a vast corpus and fine-tuning downstream tasks, excellent performance can be achieved (Zhang, Chen, Zheng, et al., 2021).

In this paper, we employ the pre-trained *bert-base-Chinese* model,[3] with the addition of a classification layer for fine-tuning. The model was pre-trained as a semantic encoder by Google Company. This model, with 110M parameters, is well-suited for processing Chinese texts. It consists of 12 layers of transformers, each with 12 attention heads, and the embedding size is 768, which enables it to capture complex patterns in noise complaints text. We fine-tune this model on our dataset of labeled noise complaints. First, the complaint text is preprocessed using the BertTokenizer. The text is then passed through the pre-trained BERT model, and the output from the final encoder layer is used as content embeddings. Subsequently, these embeddings are fed into a classification layer, which outputs the probability distribution across the four predefined categories (note that an additional category is designated for irrelevant complaints). The evaluation criteria for the model inference results include Precision, Recall, and F1 score.

Precision is the ratio of actual positive samples among those predicted as positive. Its formula is:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

where *TP* represents the number of True Positives, i.e., the instances correctly predicted as positive, and *FP* represents the number of False Positives, i.e., the instances wrongly predicted as positive.

Recall is the ratio of correctly predicted positive samples among all actual positive samples. Its formula is:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

where *FN* represents the number of False Negatives, i.e., the actual positive instances predicted as negative.

The F1 Score is the harmonic mean of precision and recall, used to measure the comprehensive performance of the model. Its formula is:

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

The F1 Score serves as our primary metric for evaluating model performance, as it takes into account both Precision and Recall, striking a balance between these two metrics.

2.3. Noise explanation based on ResNet-18 and the CAM method

Complex and densely populated urban environments are full of diverse noise sources that contribute significantly to noise exposure. Traditional methods rely solely on semantic features (e.g., proportion of cars) to identify the source of noise from an objective perspective but fail to capture the underlying relationship between noise perception and environmental features because they lack a human-centered perspective. To address this issue, we employed a pre-trained Residual Network-18 model (ResNet-18) to build the connection between subjective perception and objective environmental features.

The ResNet-18 model, which features 18 layers of convolutional neural networks, is commonly utilized in various image classification tasks. Initially trained on the comprehensive ImageNet dataset, it is highly capable of extracting intricate visual features. In this study, the ResNet-18 model underwent specific adaptations to better suit noise classification. The original classification layer, designed for 1024 different outputs, was modified to include just four output units, directly targeting the categorization of various noise types. Additionally, the model was fine-tuned on a dataset of street view images, each was annotated with a specific noise category (i.e., ''0'' represented no noise complaints and ''1'' represented the presence of noise complaints).

To deepen our understanding of how the ResNet-18 model reaches its decisions, we integrated it with the CAM method (Li et al., 2022). We were able to determine which features in an image significantly influence the model's predictions of noise categories. The computation of CAM is done by the following formula:

$$CAM = \sum_{k} w_k^c \cdot f_k(Pixel_i, Pixel_j) \tag{4}$$

[3] https://huggingface.co/google-bert/bert-base-chinese.

Fig. 3. Online crowd-sourcing annotation platform based on the doccano framework.

where (w_k^c) is the weight obtained from the ResNet-18 softmax layer corresponding to class (c) for feature map (k), and $f_k(x,y)$ is the activation of the feature map (k) at the image spatial location $(Pixel_i, Pixel_j)$.

By employing CAM, we generated heatmaps that were superimposed on the original street view images, highlighting key features that are indicative of noise, such as high-traffic zones or construction sites. The combination of ResNet-18 with CAM not only provides deeper insights into the model's decision-making processes but also helps in refining the model by identifying potential biases or inaccuracies.

2.4. Calculation of noise exposure and inequality

To simplify the analysis, we use the number of noise complaints as an indicator of noise exposure in particular residential communities. Specifically, we treated each residential community as a point and used ArcGIS tools to create a buffer zone with different radii, such as 100 m, 200 m, or 500 m. As shown in Fig. 2, we calculated the total volume of noise complaints, which represents the noise exposure, within the different radii of buffer zones. For each type of noise, the community's noise exposure coefficient E is calculated as follows:

$$E = \sum_{i=1}^{n} buffer_j \tag{5}$$

where $buffer_j$ represents the number of noise complaints within the buffer zone at distance j.

In addition, we utilize the Gini coefficient (Chen, B et al., 2022) to assess the inequality in noise exposure across different residential communities. The Gini coefficient is a commonly used indicator to measure distribution inequality and is suitable for evaluating the distribution of noise exposure. The Gini coefficient is calculated as follows:

$$Gini = \frac{n + 1 - 2\left(\sum_{i=1}^{n}(i \cdot x_i) \Big/ \sum_{i=1}^{n} x_i\right)}{n} \tag{6}$$

where n is the total number of residential communities, x_i is the noise exposure value E for community i, and $\bar{x}$ is the average noise exposure across all residential communities. Using the above formula, the absolute differences in noise exposure between every pair of communities are summed and then divided by the square of the total number of communities times the average noise exposure. This results in a value between 0 and 1, where 0 indicates complete equality of noise exposure (i.e., all communities have the same noise exposure), and 1 indicates complete inequality of noise exposure (i.e., one community has extremely high exposure while others have very low).

Furthermore, we calculated the population, aging rate (i.e., the proportion of the population over 60 years old), and building density, which are related to noise perception, propagation and generation mentioned in Section 2.3. To clarify, the population (P) is determined as the aggregate number of individuals within a given radius buffer. The aging rate (AR_i) of community i is computed as the proportion of the population over 60 years old, A_j, relative to the total population, P_j, within radius j (Equation (7)). Furthermore, the building density (BD_i) of community i is derived by dividing the area covered by buildings, B_j, by the overall buffer area, S_j, within distance j (Equation (8)).

Table 1
Noise complaint classification model accuracy.

Category	Precision	Recall	F1 Score
Overall Accuracy	0.84	–	–
Non-Noise Complaints	0.89	0.74	0.81
Traffic Noise	0.73	0.94	0.82
Industrial Noise	0.94	0.83	0.88
Living Noise	0.83	0.85	0.84

$$AR_i = \frac{A_j}{P_j} \tag{7}$$

$$BD_i = \frac{B_i}{S_i} \tag{8}$$

3. Results

3.1. Noise classification and spatial-temporal patterns

To build a sufficiently reliable training dataset, we developed an online crowdsourcing annotation platform based on the doccano framework (Fig. 3). Five volunteers were invited to label and review the data. A total of 2,596 noise complaint data were labeled, including 755 industrial noise complaints, 736 living noise complaints, 581 traffic noise complaints, and 524 noise-related complaints. Based on these labeled data, 80% of the dataset was used for model training, and 20% for testing.

Bert is a state-of-the-art model for natural language processing tasks (Devlin et al., 2019). It is particularly effective for text classification due

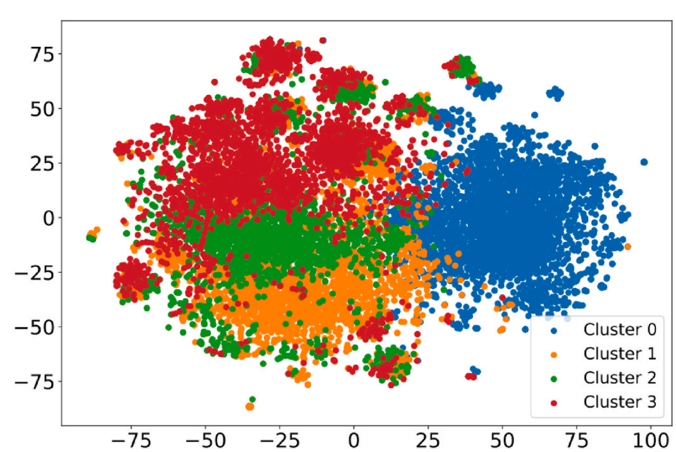

Fig. 4. Dimensionality reduction results of the semantic encoding vectors generated by the fine-tuned BERT model for noise complaints.

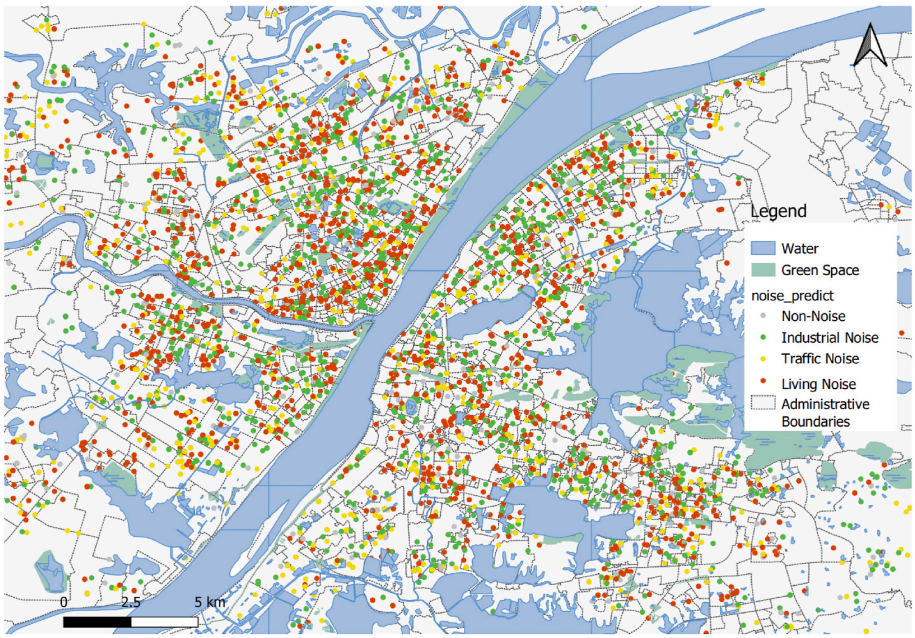

Fig. 5. Spatial distribution of predicted noise complaints using the fine-tuned model (urban residents' subjective noise perception map).

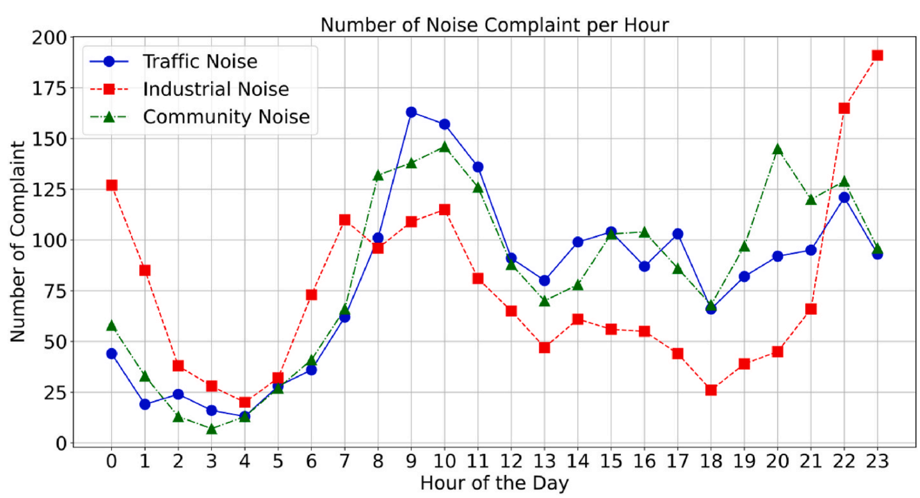

Fig. 6. Temporal distribution of different types of noise complaints predicted by the fine-tuned BERT model.

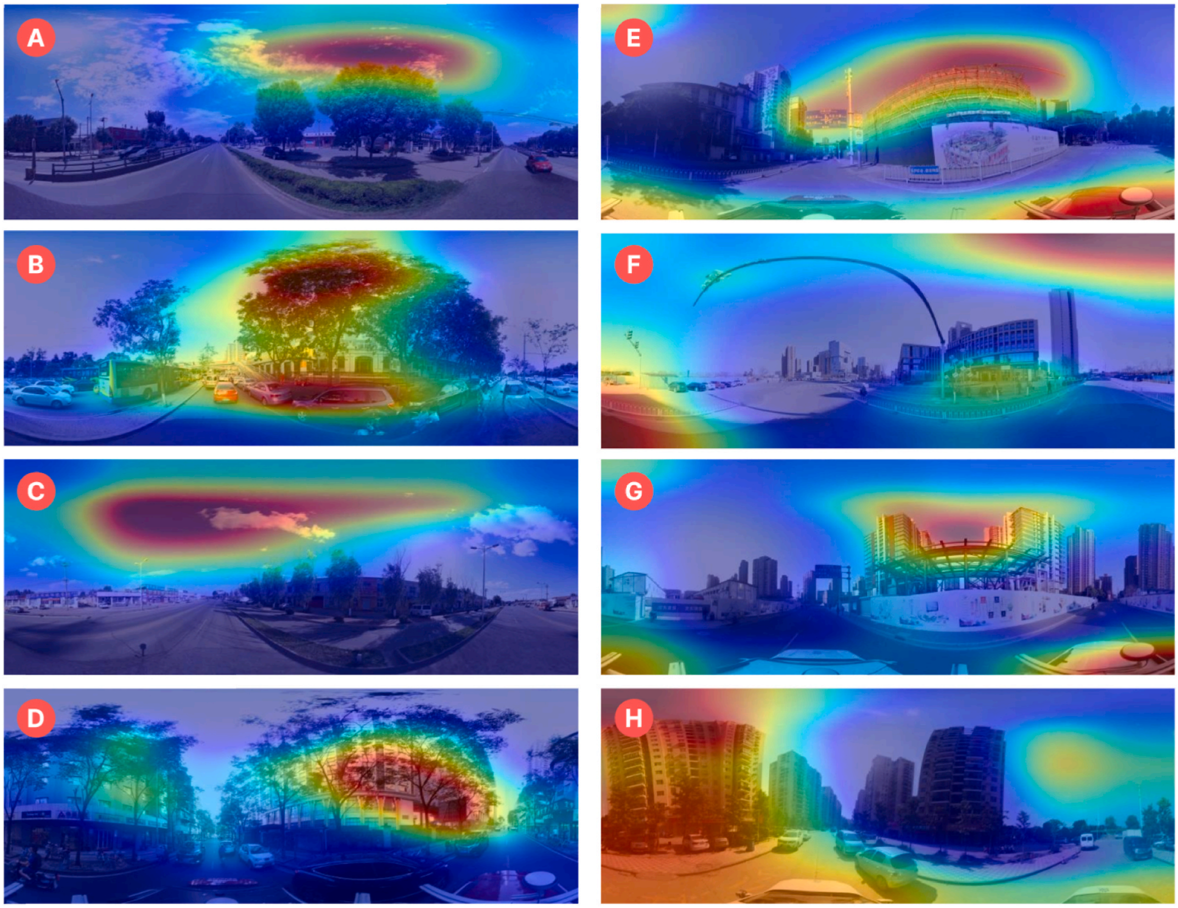

Fig. 7. Noise complaints explanation using CAM heatmaps. These heat maps clarify the dynamic visual hotspots of urban noise complaints by highlighting crucial areas where noise sources and their propagation patterns affect the model's predictions. The model predicts that street views ABCD will have no noise complaints, whereas street views EFGH will have noise complaints.

to its ability to understand the context of words in a sentence. This model helps in accurately classifying the noise complaints into relevant categories, which is crucial for understanding the specific sources and types of noise. This research fine-tuned the Bert model, and the training batch size was set to 8, and the evaluation batch size was set to 16. Additionally, the model training utilized 500 warm-up steps and a weight decay of 0.01 to prevent over-fitting, with logging at each training step. As shown in Table 1, our refined model produced acceptable results with less than 5 training epochs, in contrast to the BERT model's pre-training, which normally takes hundreds of epochs.

Among all types of noise complaints, industrial noise has the highest Precision (0.94) and F1 Score (0.88), indicating that the model is more sensitive to this type of noise, meaning that the semantic information of these noise complaints is more distinct. The overall accuracy of the model is 0.84, which is generally considered quite reliable.

The good performance of the model is as expected. We used the t-SNE (t-Distributed Stochastic Neighbor Embedding) technique for dimensionality reduction, which effectively maintains the relative positions of high-dimensional data points in two-dimensional or three-dimensional space. As shown in Fig. 4, the diagram displays the dimensionality reduction results of the semantic encoding vectors generated by the fine-tuned BERT model for noise complaints. Each point in the diagram represents a noise pollution complaint. In the semantic space, the three main types of noise complaints (i.e., traffic, industrial, and living) show distinct clustering trends. For instance, traffic noise complaints are usually concentrated in a specific area of the semantic map (cluster 0), which might be closely related to the frequent occurrence of terms associated with vehicle movement and horn sounds.

Based on this fine-tuned model, inference was conducted on the remaining nearly eight thousands unlabeled noise complaint data, and the spatial distribution of all predicted results is depicted in Fig. 5. For the purpose of analyzing the causes of the noise environment, we only selected the complaint data with location information as our primary data source for subjective noise perception. It can be observed that various types of noise are interspersed in a staggered distribution, with industrial noise and living noise being more concentrated in the main urban area. This map could also be referred to as an urban residents' subjective noise perception map. It filters out noise that has a minor impact on residents (e.g., residents will not complain about noise that does not affect their normal activities, such as construction sites equipped with adequate noise barriers), focusing only on noise that significantly affects their subjective experiences.

Table 2
Comparative statistics of environmental and socio-economic characteristics surrounding different types of noise complaints.

Feature	F-statistic	p-value	mean	variance	std-dev	skewness	kurtosis	N1	N2	N3
Pop	9.932	0	133.083	22237.634	149.123	2.939	16.602	143.474	136.051	117.892
AR	1.08	0.34	0.002	0	0.015	8.345	72.443	0.002	0.001	0.002
BD	55.057	0	0.211	0.01	0.1	0.053	-0.302	0.223	0.221	0.186
road	13.31	0	0.182	0.003	0.053	0.097	2.145	0.176	0.183	0.187
sidewalk	10.072	0	0.009	0	0.012	2.691	9.149	0.01	0.009	0.008
building	7.81	0	0.188	0.021	0.146	1.054	0.679	0.2	0.185	0.178
wall	0.887	0.412	0.005	0	0.012	6.761	60.939	0.005	0.005	0.005
fence	4.008	0.018	0.023	0.001	0.026	1.382	2.631	0.021	0.024	0.023
pole	4.497	0.011	0.007	0	0.006	0.828	0.431	0.007	0.008	0.008
traffic light	5.855	0.003	0	0	0	10.572	167.772	0	0	0
traffic sign	2.399	0.091	0.003	0	0.005	3.429	16.928	0.003	0.004	0.004
vegetation	0.033	0.967	0.233	0.031	0.176	0.574	-0.741	0.233	0.233	0.234
terrain	4.959	0.007	0.007	0	0.014	3.81	19.83	0.007	0.006	0.008
sky	3.402	0.033	0.294	0.022	0.149	0.001	-0.883	0.286	0.296	0.301
person	5.783	0.003	0.003	0	0.005	5.496	47.817	0.003	0.003	0.003
rider	5.516	0.004	0	0	0.001	6.781	65.121	0	0	0
car	9.672	0	0.039	0.001	0.031	0.904	0.738	0.041	0.038	0.036
truck	1.489	0.226	0.003	0	0.009	10.183	168.824	0.002	0.003	0.002
bus	1.505	0.222	0.001	0	0.009	14.114	213.908	0.001	0.001	0.001
train	1.179	0.308	0.001	0	0.006	28.138	945.309	0	0.001	0.001
motorcycle	14.814	0	0.001	0	0.003	8.59	95.087	0.001	0	0
bicycle	16.661	0	0.001	0	0.002	4.749	35.876	0.001	0.001	0.001

Note: *N1, N2, and N3 represent the mean values of complaints about living noise, industrial noise, and traffic noise, respectively.*

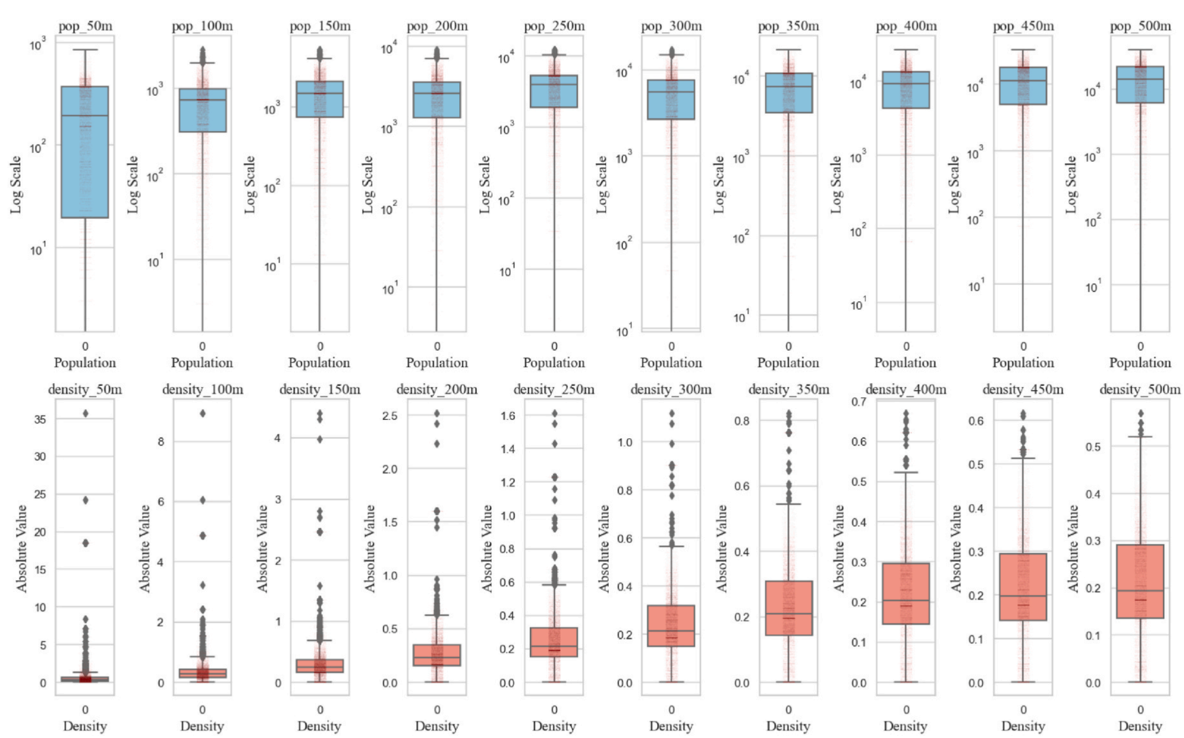

Fig. 8. Population coverage and building density around noise complaint locations. This chart illustrates the population affected by noise in different buffer zones, showing the concentration of noise complaints in urban centers where the building density exceeds 20%.

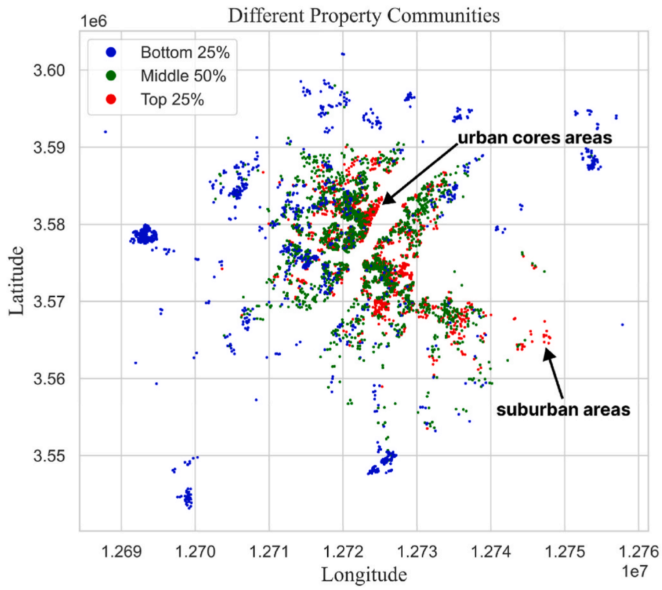

Fig. 9. The distribution of three classes of residential communities in the study area. We divided the communities into three divisions based on house prices: the top 25% were considered rich communities, the middle 50% were considered typical (or average) areas, and the bottom 25% were considered poor communities.

Further, based on the prediction results of the model, we also constructed time distribution curves for different types of noise complaints (Fig. 6). It is evident that daytime is the peak period for traffic and living noise complaints, which is closely related to people's daily activities, such as increased traffic flow during rush hours and more frequent daytime activities leading to increased living noise. Conversely, during the night, there are more complaints about industrial noise, which may be related to ongoing construction activities at night or the operational patterns of specific industrial areas.

3.2. *Noise resource explanation using RseNet-18 and CAM method*

CAM is used to identify the regions in an image that are most relevant to the classification decision (Zhou B. et al., 2016). This method helps in understanding which environmental features are associated with different types of noise, aiding in the attribution of noise complaints to specific environmental factors. To delve deeper, using the ResNet-18 model and the CAM method, this research detected the source of noise through the street view images. As shown in Fig. 7, images ABCD, predicted as scenes without noise complaints, typically show well-covered areas with vegetation, relatively quiet residential zones, and open roads. Conversely, images EFGH are predicted as having noise complaints. In Fig. 7E, the CAM heatmap emphasizes the scaffolding at a construction site, indicating that the area might be undergoing construction activities closely associated with industrial noise. The CAM heatmap in Fig. 7F focuses on pedestrian barriers along the side of the road, suggesting that traffic noise in this section might significantly affect nearby residents. As shown in Fig. 7G and H, the CAM heat maps highlight the windows on the building facades, suggesting that if the sound insulation of the windows is poor, external living noise (e.g., from large-scale events like concerts) could cause significant disturbance to the residents, thus triggering complaints.

The CAM heat maps not only focus on the noise sources but also pay attention to the paths of noise propagation, serving as key visual features in model decision-making. This method provides a valuable perspective for understanding and identifying the sources of noise.

About the noises influence on residents. Fig. 7F shows that the environmental characteristics of traffic noise include high traffic density, proximity to major roads, and the presence of traffic signals. These factors may increase stress levels, cause sleep disturbances, and elevate the risk of cardiovascular diseases for nearby residents. Fig. 7E indicates that industrial noise involves heavy machinery and ongoing construction activities, which may lead to hearing damage, irritability, and sleep disturbances among residents. Lastly, Fig. 7G illustrates that living noise (community noise), associated with densely populated residential areas, can similarly disrupt daily activities and cause sleep disturbances (Petri, D et al., 2021).

In addition, to discover the differences in how the surrounding environment influences different types of noise, we performed semantic segmentation on the street view images around the noise complaint locations using the Segformer model pre-trained on the Cityscape dataset. This model can perform semantic segmentation on images, calculating the proportions of 19 visual features such as trees, cars, and pedestrians in the image. Further, we expanded our factors to include three socioeconomic indicators that could influence or reflect the effects of noise pollution, including Pop (the total population within a 50-m radius of the location of noise complaints), AR (the aging rate within the area around the location of noise complaints), and BD (the building density within a 50-m radius of the location of noise complaints) mentioned in Section 3.4. Including these factors allows for a more comprehensive discussion of how economic and demographic variables interact with noise exposure.

In Table 2, N1, N2, and N3 represent the mean values of complaints about living noise, industrial noise, and traffic noise, respectively. It shows that there are no significant differences between the aging rate (AR), the proportion of walls, vegetation, traffic signs, and the proportion of trucks, buses and trains around different types of noise ($p < 0.05$). However, there are significant differences in other characteristics among different types of noise pollution. In particular, the population (Pop) (143.474), building density (BD) (0.223), and pixel proportion of buildings (0.200) around sources of living noise are significantly higher than other noise type surroundings.

Further, we map the residential communities affected by noise complaints and the surrounding building density and population (Fig. 8). Within a 50-m buffer zone, noise complaints typically affect hundreds of people. As the buffer distance increases to 400–500 m, the average population affected rises to over ten thousand, while the noise may have been reduced to a level below 50 dB(A) and is no longer harmful. Our calculations are based on the products of the population grid[4] and the analysis confirms the significant impact of noise exposure on residential communities. In some areas, multiple sources of noise exposure overlap, leading to considerable effects on residents' physical and mental health that cannot be ignored.

Besides, we mapped the building density (BD) around the noise complaint locations and found that the building coverage in the 400–500 m buffer size exceeded 20%. This indicates that noise complaints occur primarily in central urban areas because of the high density of buildings. There are also other noise sources in the city that are less likely to be reflected in noise complaints due to their distance from populations and dense buildings. This analysis highlights the buffer areas where urban planning (noise management) strategies could be most effectively applied to reduce the adverse effects of noise pollution.

3.3. *Community noise exposure and inequality levels*

Geospatial analysis enables the examination of spatial relationships and patterns in the data, which is particularly useful for assessing economic inequality by mapping noise complaints against socioeconomic data. To investigate the inequality in noise exposure among different residential communities, we collected the term of socio-economic data (i.e., housing price) of 9,791 residential communities. We categorized

[4] https://www.worldpop.org/.

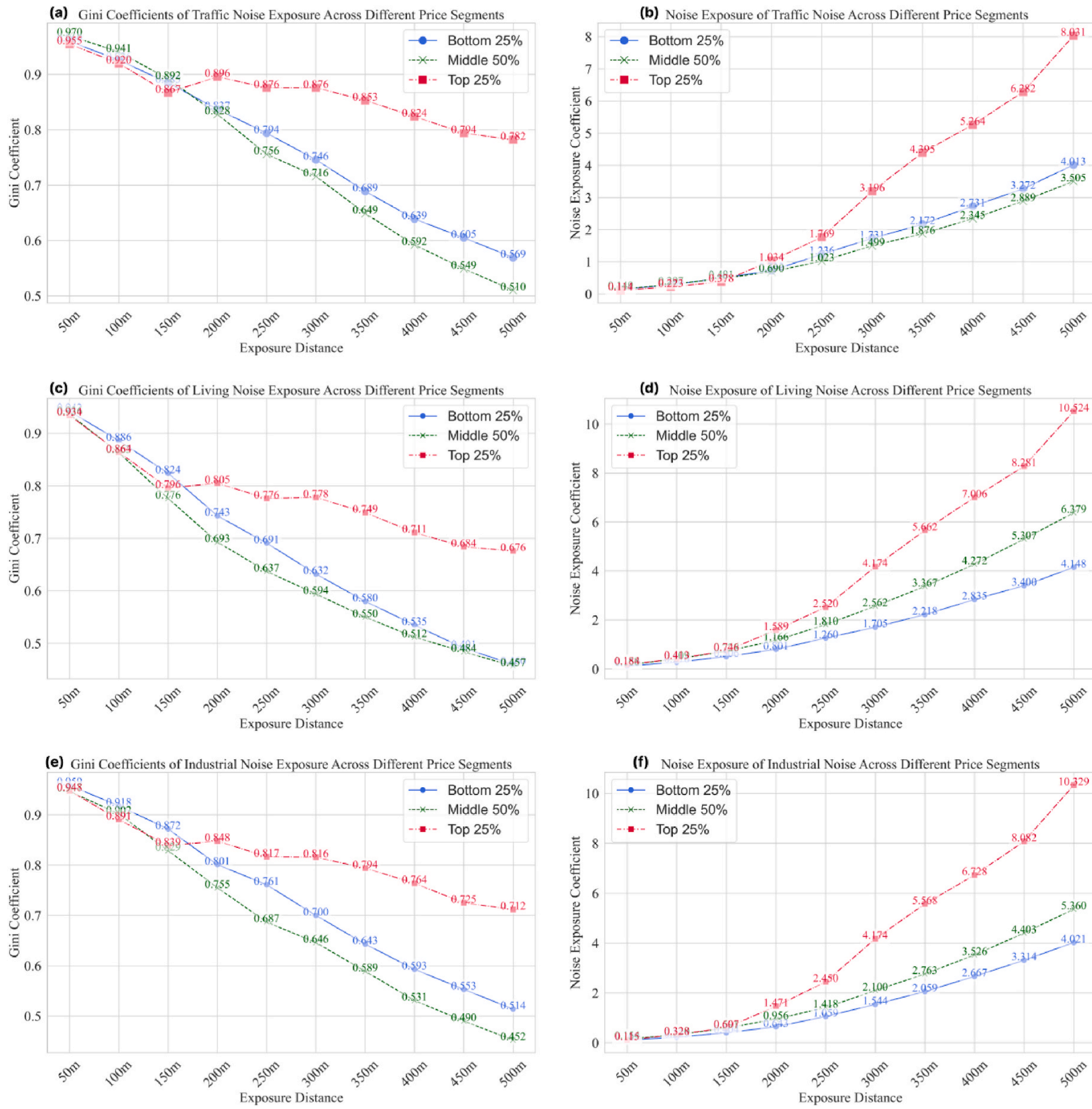

Fig. 10. Exposure levels and the Gini coefficients of three community classes facing different types of noise pollution. (a) The Gini coefficients of traffic noise exposure; (b) Exposure to traffic noise; (c) The Gini coefficients of living noise exposure; (d) Exposure to living noise; (e) The Gini coefficients of industrial noise exposure; and (f) Exposure to industrial noise.

the residential communities into three groups based on their housing prices: the top 25% as rich communities, the bottom 25% as poor communities, and the middle 50% as average communities. The distribution of these community types within the study area is shown in Fig. 9.

Fig. 10 illustrates noise exposure and inequality (i.e., Gini coefficients) for different community types (i.e., rich, poor, and average) at different buffer distances for industrial, living, and traffic noise, respectively.

The results revealed a counterintuitive phenomenon: rich communities (top 25%) may experience higher noise exposure compared to average communities (middle 50%). There are significant differences among community types, with rich communities exhibiting higher internal inequality (i.e., Gini coefficients). This situation could be attributed to several factors. As shown in Fig. 9, rich communities are typically located in urban cores or scenic suburban areas, leading to substantial differences in noise exposure between these two areas. Additionally, urban core areas are associated with busy traffic and commercial activities, contributing to higher noise exposure.

Most similar studies conducted in the United States have suggested that poor communities face more severe noise pollution than rich ones (Collins et al., 2020; Nelson-Olivieri et al., 2024). However, our empirical analysis in China leads to the opposite conclusion. This discrepancy may be due to the different stages of urbanization in the United States and China. Over the past 20 years, China has undergone rapid urbanization, with high-end communities located both in central urban areas and far suburbs (He & Zhang, 2023; Yang & Qian, 2022), resulting in significant variations in noise exposure between these areas.

Focusing on industrial noise (Fig. 10e and f), a clear trend emerges beyond the 150-m buffer zone: rich communities have higher Gini coefficients than poor communities, which in turn have higher coefficients than average communities. This indicates that rich communities exhibit greater internal differentiation and inequality (Gini coefficients of approximately 0.7–0.8) compared to other community types. In terms of absolute noise exposure, rich communities have the highest exposure, followed by average communities, with poor communities experiencing the lowest exposure.

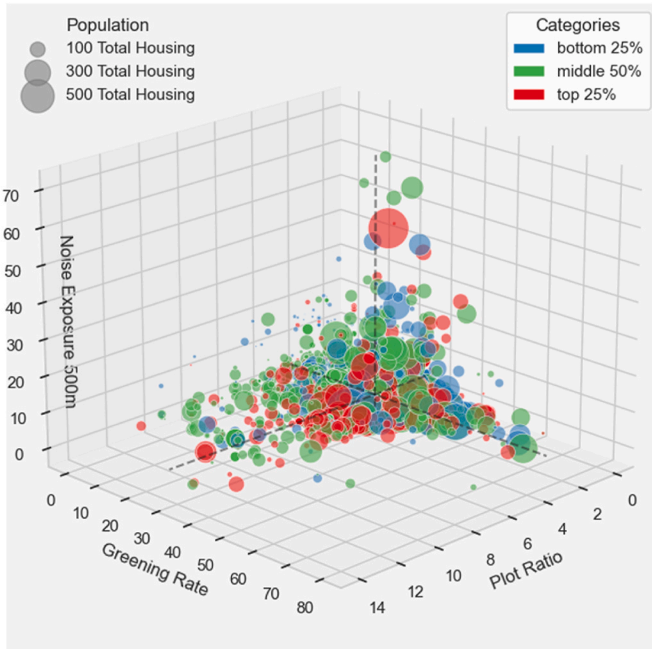

Fig. 11. Relationship between the plot ratio, the greening rate, and noise exposure within the 500m buffer. Each point represents a different property (residential community), the black line represents the median value, and the size of the points denotes the number of housing units in the community. The scatter plot illustrates the interrelationships among these factors and emphasizes the impact of housing volume. Data source: Lianjia.

Regarding residential community exposure to traffic noise and living noise, a significant difference in industrial noise exposure is that the absolute noise exposure level in poor communities is lower than that in average communities (Fig. 10a–d). However, their Gini coefficient is higher than that of the average communities, indicating that although the overall exposure level is lower, the inequality of noise exposure within poor communities is more serious. Within the poor communities, there are some areas with high noise exposure, such as those near major roads or industrial parks, which exacerbates the inequality in noise distribution. In contrast, although the overall exposure in the average communities is higher than that in poor communities (but lower than in the rich communities), the distribution is more even, resulting in a lower Gini coefficient.

Additionally, we created Fig. 11 to describe the relationship between the plot ratio, the greening rate (both from Lianjia property website), and noise exposure based on the 500m buffer. There is an interesting trend: the greening rate and exposure values display a normal distribution, with noise exposure being the highest when the residential community greening rate is at 20%. Beyond 20%, the higher the greening rate in a community, the lower the noise exposure, suggesting that more foliage or green spaces could potentially act as a buffer against noise pollution. Moreover, we found that the higher the plot ratio, the lower the noise exposure. Another point to note is that rich communities (red) have a large variance in noise exposure (and also with a higher Gini coefficient). This suggests that within wealthier areas, the quality of life related to noise pollution might vary widely depending on the specific locations and characteristics of the neighborhood. It also reveals a counterintuitive relationship between the plot ratio and noise exposure. Typically, higher plot ratios, which indicate denser buildings, might be assumed to correlate with higher noise levels due to increased human activity and closer proximity to traffic. Our findings suggest the opposite: once the plot ratio exceeds 2, the noise exposure remains consistently low across all types of residential communities. This could be due to enhanced architectural designs that incorporate sound-dampening features in denser communities.

In summary, some potential inequalities cannot be directly observed from the Gini coefficients and noise exposure values. First, there is greater inequality in noise exposure within the rich communities, as some of them are located in the convenient city center while others are located in the more beautiful and private suburbs. Second, although the noise exposure in the poor communities is not high, considering that most poor communities are located in the outer suburbs, their noise exposure is similar to that of the average communities. Taking the average and poor communities as examples, communities with housing prices in the bottom 25% are mostly distributed in the outer suburbs (Fig. 9), yet these two types of communities have similar noise exposure levels. This means that while some affluent communities in the city center enjoy more convenient transportation, shopping, and educational services, they also bear the corresponding cost of noise exposure. At the same time, the poor communities, without access to these amenities, still suffer from similar levels of noise exposure as the average communities. By combining noise exposure data with residential community distributions, we uncover counterintuitive insights into urban noise exposure and discover inequalities: 1) There is inequality in noise exposure among the rich communities, with communities located in the city center experiencing higher noise exposure. 2) Although noise exposure in the poor communities is not high, due to their distance from the city center, the noise exposure they experience is higher than expected.

4. Discussions

This study explored the impacts of different types of noise on various residential communities based on 287,529 noise complaint records from Wuhan. We classified the noise complaints into three categories (traffic noise, industrial noise, and living noise) and trained a BERT-based classification model that achieved an accuracy of more than 84%. Further, we introduced a visual model that identified the environmental features associated with different noise sources, such as construction scaffolding, sidewalks, and dense windows. The noise complaint data used in this study effectively reflect residents' subjective noise perceptions and could help produce accurate noise exposure maps, providing a reliable reference for addressing noise issues.

4.1. Noise complaints and economic inequality

A major finding of this study is that wealthier communities experienced the highest average noise levels and the most significant inequality in noise exposure. This contrasts with previous studies (e.g., Trudeau et al., 2023), which often found that poorer communities bear the brunt of noise pollution. This discrepancy may be closely related to the characteristics of China's urbanization process, where rapid development and high-density construction can lead to higher noise levels in affluent areas. Similar inequalities were observed between average and poor communities, with poorer communities experiencing higher noise levels and more unequal noise exposure, consistent with previous research (Carrier et al., 2016; Collins et al., 2019).

4.2. The patterns of noise complaints

Our research also highlights different temporal patterns of noise experiences: traffic and living noise peaks during the day, aligning with human activity patterns, whereas industrial noise complaints increase at night, likely due to ongoing construction activities. This temporal analysis provides insights into how noise impacts daily life differently across various communities. Additionally, we developed a crowd-sourced complaint labeling platform and a model for automatic complaint classification and environmental feature recognition based on pre-trained models. This system can be rapidly deployed in other cities, offering a scalable solution for noise monitoring and management.

4.3. Study limitations

This study has some limitations. First, treating noise complaints as proxies for subjective noise exposure does not account for actual noise levels. Differences in noise perception across residential communities may introduce biases in the results. Another limitation is about the noise complaint classification, the integrating features such as building characteristics, road features, and the timing of complaints are useful in improving classification accuracy. In addition, our study ignores the use of soundproofing materials and devices in buildings, especially in rich communities. These limitations should be considered in future studies.

5. Conclusion

In conclusion, our study collected a substantial amount of noise complaint data and assessed the noise exposure risks to the population in the study area. It fills a gap in research on noise exposure inequality in mainland China and reveals differences in such inequalities compared to Europe and America. Our findings underscore the importance of considering socioeconomic factors and geographical context in noise pollution research and highlight the need for targeted noise mitigation strategies to protect vulnerable populations.

CRediT authorship contribution statement

Yan Zhang: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Mei-Po Kwan:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Conceptualization. **Haoran Ma:** Writing – review & editing, Writing – original draft, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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